

Enhancing Knowledge Graph Completion with GNN Distillation and Probabilistic Interaction Modeling

Lingzhi Wang^{1,2}, [†]Pengcheng Huang², Haotian Li^{1,2}, Yuliang Wei^{1,2},
Guodong Xin^{1,2}, Rui Zhang^{1,2}, Donglin Zhang^{1,2}, Zhenzhou Ji², ^{*} Wei Wang^{1,2},

^{*} Corresponding Author, [†] Co-first Author

¹ Shandong Key Laboratory of Industrial Network Security

² School of Computer Science and Technology, Harbin Institute of Technology, Weihai 264209,

Correspondence: {23s130410, 23s030138, 24b903122, 24s030150}@stu.hit.edu.cn,

{gdxin, wei.yl, jizhenzhou,wwhit}@hit.edu.cn, lihaotian1231@gmail.com,

Abstract

Knowledge graphs (KGs) serve as fundamental structures for organizing interconnected data across diverse domains. However, most KGs remain incomplete, limiting their effectiveness in downstream applications. Knowledge graph completion (KGC) aims to address this issue by inferring missing links, but existing methods face critical challenges: deep graph neural networks (GNNs) suffer from over-smoothing, while embedding-based models fail to capture abstract relational features. This study aims to overcome these limitations by proposing a unified framework that integrates GNN distillation and abstract probabilistic interaction modeling (APIM). GNN distillation approach introduces an iterative message-feature filtering process to mitigate over-smoothing, preserving the discriminative power of node representations. APIM module complements this by learning structured, abstract interaction patterns through probabilistic signatures and transition matrices, allowing for a richer, more flexible representation of entity and relation interactions. We apply these methods to GNN-based models and the APIM to embedding-based KGC models, conducting extensive evaluations on the widely used WN18RR and FB15K-237 datasets. Our results demonstrate significant performance gains over baseline models, showcasing the effectiveness of the proposed techniques. The findings highlight the importance of both controlling information propagation and leveraging structured probabilistic modeling, offering new avenues for advancing knowledge graph completion. And our codes are available at https://anonymous.4open.science/r/APIM_and_GNN-Distillation-461C

1 Introduction

Knowledge graphs (KGs)(Pan et al., 2017) are a type of semantic representation of the knowledge in the form of triples, where each triple consists of a subject, a predicate, and an object. Large-scale

KGs, such as Wikidata(Vrandečić and Krötzsch, 2014), DBpedia(Lehmann et al., 2015), and Freebase(Bollacker et al., 2008), have been generated and successfully applied in various applications such as question answering(Cui et al., 2023; Wang et al., 2023), information retrieval(Fei et al., 2021; Dutkiewicz and Jędrzejek, 2024), and natural language processing(Hu et al., 2024). However, most of the KGs are incomplete(Bollacker et al., 2008), and they need to be completed to enable various applications. Therefore, knowledge graph completion (KGC) is the task of predicting missing facts or triples in a knowledge graph (KG) based on the existing facts or triples(Shen et al., 2022). The most important step for KGC better performance is to capture the suitable characteristics of the entities and relations in the KGs.

Recently, there have been several works on KGC, such as the Graph Neural Networks (GNNs) models based the intrinsic graph-structure of KGs(Li et al., 2023) and the embedding models, particularly large-scale language model (LLM) based methods generated the KGs semantic representation(Wang et al., 2022).

The GNNs-based modules iteratively aggregating information from neighboring nodes to learn low-dimensional representations of entities and relations. Unlike traditional embeddings approaches (e.g., TransE(Bordes et al., 2013) ComplEx(Trouillon et al., 2016), Tucker(Balažević et al., 2019)) for KGs, the GNNs-based methods take advantage of the topology of the knowledge graph, thereby enhancing the representations with contextual information(Hamilton et al., 2017). In the context of knowledge graph completion, a widely recognized challenge is to capture and integrate relational information while preserving the the discriminative features of entities. For instance, the Relational Graph Convolutional Network (RGCNs)(Schlichtkrull et al., 2018). By modeling each relation type separately, RGCNs can bet-

ter capture the semantic nuances across different types of edges. More broadly, GNN variants such as Graph SAGE(Hamilton et al., 2017) and Graph Attention Networks (GATs)(Veličković et al., 2017; Nathani et al., 2019) have also been adapted for KGs, offering inductive and attention-based mechanisms to aggregate neighborhood entities’ features.

Problem 1. A critical limitation of deep GNNs in KGs applications is over-smoothing, where repeated message-passing operations cause node representations to become indistinguishable, degrading model performance(Li et al., 2018; Oono and Suzuki, 2019).

The LLM-based methods adapt the pre-trained language model (e.g., BERT(Devlin et al., 2019), ChatGpt(Nazir and Wang, 2023)) to leverage the semantic information of extra entities description. In these method, each triple (h, r, t) is converted into a textual sequence, which often by concatenating the textual description of the head entity h , the relation r , and the tail entity t . The combined sequence is then fed into the pre-trained language model to produce a contextual embedding, which can be used to predicate the missing triples.

Problem 2. Although pre-trained language models can effectively capture the semantic nuances of auxiliary entity descriptions, they fall short in modeling the higher-dimensional, abstract features necessary for knowledge graph completion. In essence, these models do not adequately represent the sophisticated, latent relational patterns—beyond mere local and global structures—that are critical for capturing the intricate interplay between entities and relations in knowledge graphs.

Present work. In this paper, we propose a GNN distillation method and an abstract probabilistic interaction modeling (APIM) method to address the aforementioned challenges. In contrast to standard distillation approaches, our GNN distillation method incorporates an iterative message-feature filtering process at each GNN layer. By filtering and propagating only the most informative features, this technique effectively mitigates over-smoothing, thereby enhancing the embeddings’ representational capacity and preserving higher-order relational cues within the knowledge graph. In parallel, our abstract features capture method models the interaction probability of abstract features across different entities and computes the expected value of these feature-mediated interactions, thereby capturing both local and global structural information. Specifically, we apply both methods to traditional

GNN-based KGC models and employ the abstract features capture method in traditional embedding-based KGC models. Empirical evaluations demonstrate that our proposed approaches outperform their respective baselines on knowledge graph completion tasks.

2 Preliminaries

2.1 Knowledge graph completion (KGC)

Knowledge Graph Completion (KGC) constitutes a pivotal task in knowledge representation learning, dedicated to predicting missing connections between entities within incompletely observed knowledge graphs (KGs). Formally, given a KG defined as $\mathcal{G} = \{(h, r, t)\} \in \mathcal{E} \times \mathcal{R} \times \mathcal{E}$, where \mathcal{E} and \mathcal{R} denote the entity set and relation type set respectively, the KGC task involves inferring plausible triples for masked positions in either head or tail entity slots(Shen et al., 2022), expressed as (h, r, \cdot) or (\cdot, r, t) . The standard evaluation protocol requires the model to rank all candidate entities \mathcal{E} based on a learned scoring function $f : \mathcal{E} \times \mathcal{R} \times \mathcal{E} \rightarrow \mathbb{R}$, where \mathbb{R} is a real-valued score. For a given query (h, r, \cdot) or (\cdot, r, t) , the model computes the plausibility $f(h, r, t')$ or $f(h', r, t)$ for each candidate entity $t' \in \mathcal{E}$ or $h' \in \mathcal{E}$, respectively. The candidate with maximal score is selected as the optimal completion, following the closed-world assumption(Oh et al., 2022).

2.2 GNN-based KGC methods

The GNN-based KGC methods have emerged as a dominant paradigm in KGC, primarily categorized into two types: Message Passing Neural Networks (MPNNs) and Path-based methods. In this work, we focus on the MPNNs-based methods, which operate on the principle of iterative neighborhood aggregation, where entity representations are updated by propagating a transforming information from connected neighbors.

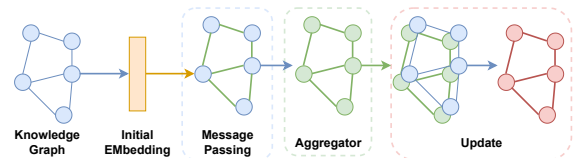


Figure 1: A general structure of the MPNNs-based KGC methods.

We demonstrate the general structure of the MPNNs-based KGC methods in Figure 1. This

framework is formally defined by three components:

$$\begin{aligned} \text{Message} : m_{ij}^{(l)} &= \phi \left(h_i^{(l-1)}, h_j^{(l-1)}, r_{ij} \right) \\ \text{Aggregation} : M_i^{(l)} &= \bigoplus_{j \in \mathcal{N}(i)} m_{ij}^{(l)} \\ \text{Update} : h_i^{(l)} &= \psi \left(h_i^{(l-1)}, M_i^{(l)} \right) \end{aligned} \quad (1)$$

where ϕ , \bigoplus , and ψ denote message functions, permutation-invariant aggregator, and update functions, respectively.

2.3 Embedding-based KGC methods

Embedding-based approaches to KGC learn low-dimensional representations for both entities and relations within a shared latent space. Typically, these methods adhere to a common training pipeline: each entity and relation is first initialized with a learnable embedding, either randomly or via pre-training; thereafter, a margin-based or cross-entropy loss is employed to differentiate positive triples from negative samples generated through random replacement of head or tail entities. Inference is performed by ranking all candidate entities according to the model’s scoring function and selecting the highest-scoring candidate as the prediction. These approaches can be broadly classified into three categories: translational distance models, bilinear models, and neural network-based models. Neural network-based models, despite being potentially more computationally intensive, offer greater flexibility and expressiveness, enabling them to capture intricate relational patterns and achieve superior performance on complex or large-scale knowledge graphs. Furthermore, pre-trained language models have been leveraged in KGC to generate high-quality textual representations that serve as valuable inputs, further enhancing model capabilities. Consequently, in this paper, we focus on neural network-based models, which represent the state-of-the-art in knowledge graph completion.

3 Methodologys

3.1 GNN distillation method

Traditional GNNs often rely on iterative message passing, where each node (entity) aggregates information from its neighbors. As we increase the number of layers, representations of different entities may converge to similar values—an effect known as over-smoothing. The GNN distillation method

is designed to tackle this problem by introducing a feature distillation step that filters and refines message signals in each GNN layer, ensuring entities maintain more discriminative embeddings.

We start with a standard GNN architecture (e.g., GCN, GAT, RGCN). During each forward pass at layer l , every node i receives a message from its neighbors $\mathcal{N}(i)$ and aggregates them as the Equation 1. After receiving the initial aggregated messages, a feature distillation operator is applied to filter out less informative and dampens or eliminates features that contribute to over-smoothing. Formally, let $m_i^{(l)}$ denote the message for node i at layer l . The operator outputs a distilled message $\tilde{m}_i^{(l)}$ based on an importance score:

$$\tilde{m}_i^{(l)} = \text{Distill}(m_i^{(l)}; \alpha_i^{(l)}) \quad (2)$$

where $\alpha_i^{(l)}$ are parameters that control the distillation ratio. The distillation process repeats multiple rounds within the same layer. Each round reevaluates the messages, removing or down-weighting redundant features and retaining only those deemed most important. Mathematically, at the k -th iteration of distillation (where $k \in \{1, \dots, \mathbb{K}\}$) with layer l , the refined message is computed as:

$$\tilde{m}_i^{(l)} = \text{Distill}(\tilde{m}_i^{(l,k-1)}; \alpha_i^{(l,k)}) \quad (3)$$

with $\tilde{m}_i^{(l,0)} = \tilde{m}_i^{(l)}$ serving as the initial input for round 1. To ensure we gradually reduce the amount of message information and avoid abruptly dropping too much signal, we adopt a linear exponential decay schedule that determines how many features are retained at each round:

$$\alpha^{(k)} = \begin{cases} \alpha_{start} - (k-1)\Delta, & \text{(linear decay)} \\ \alpha_{start} \cdot \gamma^{(k-1)}, & \text{(exponential decay)} \end{cases} \quad (4)$$

where α^k indicates the proportion of features retained or the threshold for importance scoring at round k , and Δ and γ are hyperparameters. This progressive filtering keeps the most critical features while discarding increasingly unhelpful or redundant signals. The node representation then incorporates the distilled message $\tilde{m}_i^{(l,k)}$ (i.e., after the final round of distillation), update node representations via:

$$h_i^{(l)} = \gamma \left(h_i^{(l-1)}, \tilde{m}_i^{(l,K)} \right) \quad (5)$$

As shown in Figure 2, by filtering out repetitive and uninformative message components, GNN

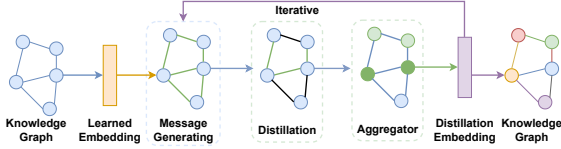


Figure 2: The visualisation of the GNN Distillation method.

distillation preserves feature diversity across different entities. This helps nodes maintain more discriminative features, rather than converging to nearly identical vectors. The iterative message filtering ensures that nodes still benefit from aggregated information (global context) but do not over-absorb neighbor features to the point of losing local uniqueness.

The distillation operator can be integrated into various GNN frameworks (GCN, GAT, RGCN) by adjusting the filtering mechanism or the decay schedule. It minimally impacts the model’s overall complexity while offering robust control over message propagation.

3.2 The abstract probabilistic interaction modeling (APIM) method

APIM introduces a probabilistic interaction paradigm that explicitly models entity-relation interactions through learnable abstract patterns. For each entity $e \in \mathcal{E}$, we learn a probabilistic interaction signature:

$$\mathbf{a}_e = \sigma(\mathbf{W}_a \mathbf{h}_e) \in [0, 1]^K \quad (6)$$

where σ is the sigmoid function, $\mathbf{h}_e \in \mathbb{R}^d$ is the entity embedding, \mathbf{W}_a is a trainable projection matrix, and K denotes the number of latent interaction modes. This step encodes how entities probabilistically engage in different interaction modes.

To focus on the most salient interaction patterns, we retain only the top-k modes for each entity:

$$\tilde{\mathbf{a}}_e = \text{TopK}(\mathbf{a}_e, k) \odot \mathbf{a}_e \quad (7)$$

where $\text{TopK}(\cdot, k)$ generates a binary mask preserving the indices of the k largest values in \mathbf{a}_e , and \odot denotes element-wise multiplication. This sparsification reduces noise from low-probability modes while maintaining gradient flow through the masked values.

In parallel, for each relation $r \in \mathcal{R}$ maintains a matrix:

$$\mathbf{P}_r[i, j] = P(\text{mode}_i \rightarrow \text{mode}_j \mid r) \quad (8)$$

where $\mathbf{P}_r \in \mathbb{R}^{K \times K}$ represent transition probabilities between interaction modes conditioned on relation r . Matrices are normalized via tanh:

$$\mathbf{P}_r = \tanh(\Theta_r), \quad \Theta_r \in \mathbb{R}^{K \times K} \quad (9)$$

where Θ_r is the trainable projection matrix of relation r . The values of \mathbf{P}_r represent the positive and negative probabilistic interactions between entity modes, respectively.

The triple score is then computed as the expectation of these interactions, combining the abstract interaction vectors with the transition matrix:

$$f(h, r, t) = \tilde{\mathbf{a}}_h^T \mathbf{P}_r \tilde{\mathbf{a}}_t \quad (10)$$

This formulation models entity interactions as weighted combinations of latent relational patterns, providing a flexible framework for capturing complex relational dynamics.

During training, the APIM module is trained in an end-to-end manner with the loss function:

$$\begin{aligned} \mathcal{L}_{\text{APIM}} = & - \sum_{(h,r,t) \in \mathcal{T}} [y_{hrt} \log \sigma(f_{\text{APIM}}(h, r, t)) \\ & + (1 - y_{hrt}) \log(1 - \sigma(f_{\text{APIM}}(h, r, t)))] \\ & + \lambda \cdot \|\mathbf{P}_r\|_F^2, \end{aligned} \quad (11)$$

where y_{hrt} denotes the ground-truth label for the triple, and $\sigma(\cdot)$ represents the sigmoid function. The term $\lambda \cdot \|\mathbf{P}_r\|_F^2$ prevents overfitting by constraining the magnitude of probability transition matrices, maintains numerical stability and approximates the effect of implicit distribution alignment through gradient-driven learning.

Generally, the TopK selection aligns with the *information bottleneck principle* (Cao et al., 2023), filtering irrelevant interaction modes to prevent overfitting. Although the learned sparse signatures $\tilde{\mathbf{a}}_e$ do not provide immediate interpretability of the underlying interaction patterns, they effectively model latent modes that capture complex relational structures. This abstraction enables the framework to generalize across diverse knowledge graph domains, providing a systematic approach to handle high-dimensional interactions.

3.3 The GNN-based models enhancement

In traditional models such as KB-GAT, RGCN, and ComPGCN, node embeddings are iteratively refined through neighborhood aggregation. Our GNN distillation method is incorporated into each GNN

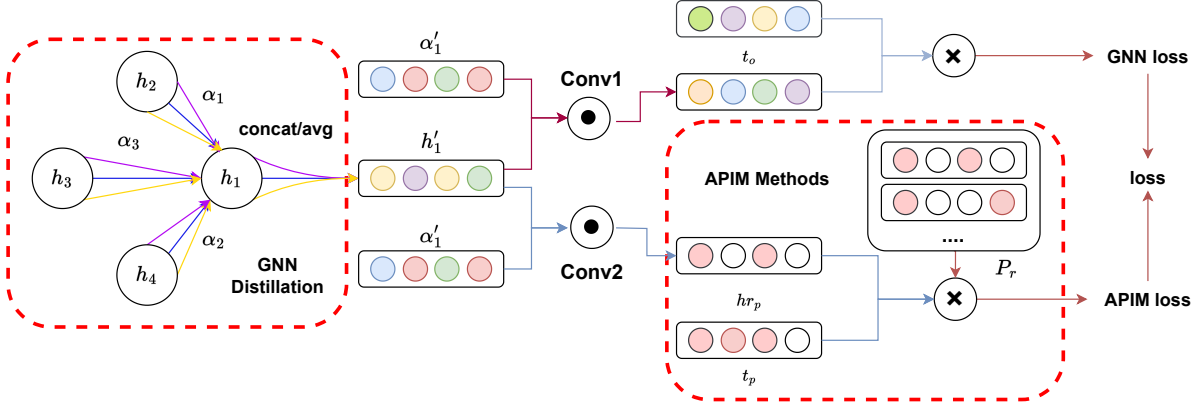


Figure 3: The enhanced KB-GAT framework integrates a GNN distillation module that refines message representations by combining them with attention weights α and an APIM module that models abstract interaction patterns. In the diagram, \otimes denotes matrix multiplication, while \odot represents the GCN aggregation operation.

layer to counteract the over-smoothing problem. For instance, in KB-GAT the attention mechanism is modified using a distillation operator into the message-passing process as shown in Figure 3. Concretely, before computing the attention weights as in (Veličković et al., 2017), the neighbor messages $m_{ij}^{(l)}$ are subjected to an iterative filtering process that yields distilled messages $\tilde{m}_i^{(l,K)}$. These distilled messages are then used in place of the original aggregated information, ensuring that only the most discriminative features are propagated. Similarly, in RGCN (Schlichtkrull et al., 2018), which aggregates information in a relation-specific manner, the distillation operator refines the aggregation process by dynamically attenuating redundant features. In ComPGCN, where compositional interactions are central to capturing higher-order relational patterns, the distillation process further enhances the model’s ability to preserve interaction-specific signals without succumbing to the over-smoothing that often plagues deeper layers (Li et al., 2018; Oono and Suzuki, 2019).

Concurrently, the APIM module is appended to the architecture following the final GNN layer. Each entity’s distilled embedding is transformed into an abstract probabilistic signature as Equation 6, where each relation r is endowed with a trainable transition matrix \mathbf{P}_r that encodes inter-modal interactions. The triple score is computed as Equation 10, thereby complementing the local structural information captured by the GNN with global abstract interaction patterns.

The enhanced models are trained under a joint optimization framework that balances the conven-

tional GNN-based loss with an auxiliary loss imposed by the APIM module. Specifically, the overall loss function is formulated as:

$$\mathcal{L} = \mathcal{L}_{\text{GNN Distillation}} + \lambda_{\text{APIM}} \mathcal{L}_{\text{APIM}} \quad (12)$$

where $\mathcal{L}_{\text{GNN Distillation}}$ represents the standard margin-based or cross-entropy loss used in enhanced GNN models (KB-GAT, RGCN, and ComPGCN) to discriminate positive triples from negative samples. The auxiliary term $\mathcal{L}_{\text{APIM}}$, defined as cross-entropy loss (Equation 11), aligns the learned abstract interaction signatures with expected relational patterns. The hyperparameter λ_{APIM} controls the relative contribution of the APIM component to the overall loss.

By integrating the GNN distillation into the KB-GAT, RGCN, and ComPGCN frameworks, our approach effectively mitigating over-smoothing by preserving discriminative local features through iterative message filtering.

3.4 The Embedding-based models enhancement

In addition to the improvements in GNN-based KGC methods, we extend the Abstract Probabilistic Interaction Modeling (APIM) mechanism to enhance recent state-of-the-art embedding-based methods for knowledge graph completion. Embedding-based approaches, such as TransE (Bordes et al., 2013) and ComplEx (Trouillon et al., 2016), typically learn fixed vector representations for entities and relations by optimizing a scoring function. Our enhancement integrates APIM into these models to capture abstract interaction pat-

terns, thereby enriching the learned representations with additional structural and semantic cues. Within the embedding-based paradigm, each entity embedding h_e is transformed into an abstract probabilistic signature via Equation 6. Each relation r is assigned a transition matrix \mathbf{P}_r , which encodes the latent interaction modes between entities. The APIM score for a given triple (h, r, t) is computed as Equation 10. This score is designed to complement the original embedding-based scoring function by explicitly modeling the probabilistic interactions underlying entity-relation pairs.

The overall training objective for the enhanced embedding-based model combines the original loss function \mathcal{L}_{Emb} (which is typically formulated as a margin-based or cross-entropy loss (Bordes et al., 2013; Trouillon et al., 2016)) with an auxiliary loss component associated with the APIM module. In our framework, the APIM-derived score is directly incorporated into the loss computation as the Equation 11. The overall loss is then defined as:

$$\mathcal{L} = \mathcal{L}_{\text{Emb}} + \lambda_{\text{APIM}} \mathcal{L}_{\text{APIM}} \quad (13)$$

with λ_{APIM} serving as a hyperparameter that controls the contribution of the APIM module relative to the original embedding-based loss. Through backpropagation, the gradients computed from this combined loss update both the original embedding parameters and the APIM-specific parameters (i.e., \mathbf{W}_a and \mathbf{P}_r), thereby enabling the model to jointly optimize for traditional embedding fidelity and abstract interaction modeling.

By integrating the APIM mechanism, the embedding-based methods benefit from an enriched representation space that more effectively captures complex relational patterns.

Empirical results (detailed in Section 4) consistently show that our enhanced model surpasses its baseline counterparts, thereby validating the effectiveness of integrating APIM into embedding-based methods and GNN distillation into GNN-based knowledge graph completion frameworks.

4 Experiments

4.1 Experiments setup

Dataset WN18RR (Toutanova and Chen, 2015) and FB15K-237 (Dettmers et al., 2018) are widely adopted for evaluating relational reasoning capabilities. WN18RR contains hierarchical lexical relations with high semantic ambiguity, while FB15K-237 features diverse real-world relations with sig-

nificant long-tail distributions. Statistics are summarized in Appendix A.

Evaluation Metrics Following standard practice in KGC (Bordes et al., 2013), our models are evaluated using the entity ranking task. For each test triple (h, r, t) , we perform tail entity prediction by ranking all candidate entities given h and r and similarly for head entity prediction. Subsequently, we evaluate the prediction performance using rank-based metrics—specifically, the Mean Reciprocal Rank (MRR) and Hits@N. In our experiments, we consider $N \in \{1, 3, 10\}$ for model evaluation. Detailed definitions of MRR and Hits@N are provided in Appendix B.

Hyperparameters For GNN-based models, our framework employs a 4-layer GNN architecture with 100-dimensional initial embeddings expanded to 200-dimensional hidden representations. To balance model depth and assess the impact of GNN distillation on mitigating over-smoothing, we implement a linear decay distillation schedule (see Appendix C for experimental details) as defined by Equation 4, using $\alpha_{\text{start}} = 1.0$, $k \in [2, 5]$, and $\Delta = 0.2$. For all models, the APIM module utilizes 100-dimensional probabilistic transition matrices \mathbf{P}_r initialized via Xavier normal distribution, enhanced by top-20 mode selection to preserve $\geq 85\%$ signature energy ($\|\tilde{\mathbf{a}}_e\|_1 / \|\mathbf{a}_e\|_1$) while eliminating noisy interactions, with experiments and proofs in Appendix D.

4.2 Main results and analysis

It is worth noting that our framework employs a 4-layer GNN architecture. This design choice allows us to systematically evaluate the effectiveness of the GNN distillation approach. By setting the depth to twice the commonly observed optimal number of GNN layers, we aim to better demonstrate how distillation mitigates over-smoothing and enhances the quality of node representations. Table 1 presents the performance comparison of our proposed methods (APIM, GNN Distillation, and their combination MERGE) against baseline models on WN18RR and FB15K-237. We summarized the key observation from the experiments:

Observation 1 *The proposed methods (APIM and GNN Distillation) significantly achieve comparable performance to their corresponding.*

The proposed APIM and GNN Distillation methods demonstrate consistent and significant improvements across all evaluated architectures. APIM enhances relational reasoning by modeling latent

Model	WN18RR				FB15K-237			
	MRR	Hit@1	Hit@3	Hit@10	MRR	Hit@1	Hit@3	Hit@10
KB-GAT	0.464	0.427	0.482	0.537	0.353	0.261	0.389	0.537
KB-GAT-APIM	0.478	0.443	0.498	0.546	0.358	0.265	0.393	<u>0.540</u>
KB-GAT-DIST	<u>0.469</u>	0.434	0.483	0.544	<u>0.359</u>	<u>0.269</u>	0.392	0.539
KB-GAT-MERG	0.466	<u>0.434</u>	<u>0.488</u>	0.538	0.362	0.270	0.396	0.549
RGCN	0.426	0.400	0.436	0.476	0.319	0.231	0.349	0.496
RGCN-APIM	<u>0.437</u>	0.406	<u>0.448</u>	<u>0.502</u>	0.345	<u>0.251</u>	0.382	0.532
RGCN-DIST	0.455	0.426	0.465	0.514	0.337	0.245	0.369	0.521
RGCN-MERG	0.436	<u>0.411</u>	0.444	0.482	<u>0.344</u>	0.253	<u>0.377</u>	<u>0.529</u>
CompGCN	0.442	0.416	0.450	0.495	0.329	0.241	0.361	0.509
CompGCN-APIM	0.472	0.440	0.484	0.531	0.338	0.245	0.373	0.526
CompGCN-DIST	<u>0.466</u>	<u>0.436</u>	<u>0.477</u>	<u>0.528</u>	<u>0.348</u>	<u>0.255</u>	0.383	<u>0.535</u>
CompGCN-MERG	0.444	0.414	0.454	0.502	0.350	0.258	<u>0.382</u>	0.537
Simkgc	<u>0.626</u>	<u>0.559</u>	<u>0.718</u>	0.819	<u>0.334</u>	<u>0.246</u>	<u>0.360</u>	<u>0.513</u>
Simkgc-APIM	0.658	0.566	0.723	<u>0.816</u>	0.335	0.248	0.362	0.514

Table 1: Main results of the WN18RR and FB15K-237 datasets experiments. The best results for each model are shown in **bold** and the second best results are underlined. APIM and DIST denote the addition of the APIM and GNN distillation methods, respectively. The MERG denotes the addition of the APIM and GNN distillation methods with the addition of the merging strategy. The results are averaged over 5 runs for each model.

interaction patterns, yielding superior performance in both traditional GNNs and pretrained language model-based frameworks. For instance, APIM-integrated variants outperform their base models across all metrics, with particularly notable gains in hierarchical relation prediction. Concurrently, GNN Distillation effectively mitigates over-smoothing in deep architectures, preserving entity distinctiveness while maintaining global structural awareness. This dual capability addresses fundamental limitations in existing KGs representation learning paradigms.

Observation 2 *The methods merged variant (MERGE) achieves synergistic performance.*

The merged variant (APIM + GNN Distillation) achieves performance exceeding the additive effects of individual components. This synergy arises from complementary mechanisms: while APIM captures high-level probabilistic interactions, GNN Distillation ensures local feature fidelity. The merged framework exhibits robust generalization across relation types establishing better results on both sparse and densely connected subgraphs.

4.3 Ablation experiments

We conduct comprehensive ablation experiments to disentangle the impact of key hyperparameters on

model performance. In particular, we vary (i) the number of retained dimensions for the APIM entity interaction modes and (ii) the filtering ratio in the GNN distillation process. These systematic investigation enables us to quantify how these hyperparameters affect the overall effectiveness of the models.

The first ablation study focuses on the influence of the retention parameter—referred to as “Top-K” (where K corresponds to the number of top dimensions retained)—within the APIM module. Four settings were examined: Top5, Top10, Top20, and Top50 as shown in Figure 4. The ablation experiments reveal that a moderate retention setting, specifically retaining approximately 20 top dimensions, consistently yields the best performance across all models. For instance, KB-GAT, RGCN, and CompGCN all exhibit notable improvements in MRR and Hits1, Hits3, and Hits10 when transitioning from lower retention settings (e.g., Top5 or Top10) to Top20, whereas further increasing the retention to Top50 leads to a slight degradation in performance. A similar trend is observed in the Simkgc model, where MRR peaks at Top20 before declining at Top50. These findings suggest that retaining around 20 key dimensions effectively captures the salient interaction modes while filtering

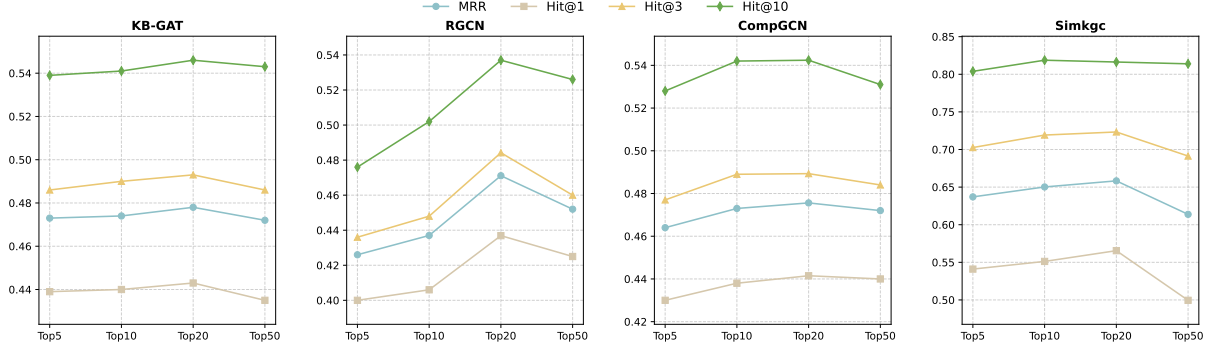


Figure 4: Impact of APIM’s **Top-K** mode retention thresholds on KGC performance (WN18RR)

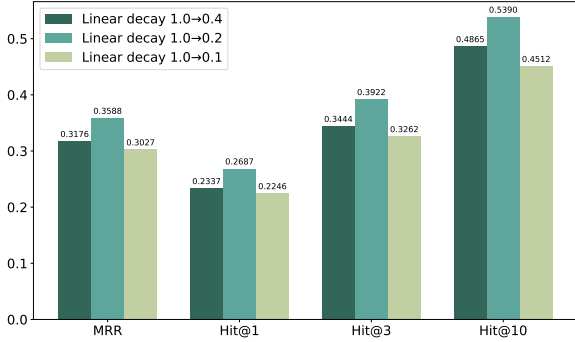


Figure 5: Impact of GNN Distillation’s filtering ratio on KB-GAT performance (FB15K-237)

out redundant or noisy features, thus striking an optimal balance and maximizing the overall performance of the knowledge graph completion models.

The second ablation study investigates the impact of the filtering ratio in the GNN distillation process on the performance of the KB-GAT model using the FB15K-237 dataset. Specifically, we compare three linear decay settings—decaying the filtering parameter from 1.0 to 0.4, from 1.0 to 0.2, and from 1.0 to 0.1. As illustrated in Figure 5, the experimental results indicate that the setting with a linear decay from 1.0 to 0.2 achieves the best performance, yielding scores of 0.3588 for MRR, 0.2687 for Hit@1, 0.3922 for Hit@3, and 0.5390 for Hit@10. In contrast, the more aggressive decay (from 1.0 to 0.1) results in a notable drop in performance, while the milder decay (from 1.0 to 0.4) also underperforms relative to the moderate setting. These findings suggest that a moderate filtering ratio effectively balances the elimination of redundant features with the retention of essential information, thereby maximizing the overall performance of the model.

5 Discussion

Key Findings: Our experiments indicate that retaining around 20 top dimensions in the APIM module and employing a moderate filtering ratio (linear decay from 1.0 to 0.4) in GNN distillation consistently yield the best performance across multiple models, effectively capturing salient interaction patterns while mitigating over-smoothing.

Practical Implications: These results demonstrate that precise tuning of the retention parameter and filtering ratio can substantially enhance model interpretability and predictive accuracy in knowledge graph completion, providing a practical framework for deploying robust KGC systems in real-world applications.

Implications for Future Research: Future work should focus on developing adaptive mechanisms for hyperparameter tuning and exploring the integration of these methods with complementary techniques, as well as validating their effectiveness on larger and more diverse datasets.

6 Conclusion

In this paper, we have introduced two complementary methods—GNN distillation and (APIM)—to address the challenges of over-smoothing and abstract feature incompleteness in knowledge graph completion. Our extensive experiments on standard benchmarks (WN18RR and FB15K-237) demonstrate that integrating these techniques into existing GNN-based and embedding-based frameworks significantly improves performance by enhancing the discriminative capacity of node representations and capturing complex relational interactions. The proposed approaches not only advance the better performance in KGC but also provide a robust framework for future research in knowledge representation learning.

Acknowledgments

This work was supported by the Key Laboratory of Cognitive Intelligence and Content Security, Ministry of Education (Grant No. RZZN202414), the Key Research and Development Program of Shandong Province (Grant No. 2023CXPT065), and the National Natural Science Foundation of China (Grant No. 62272129).

Limitation

While the proposed framework incorporating GNN distillation and APIM has demonstrated significant improvements in knowledge graph completion tasks, there are several limitations that warrant further investigation. First, the proposed methods rely on specific hyperparameter settings, such as the decay rate in GNN distillation and the number of top dimensions retained in APIM, which may require fine-tuning for different domains or tasks. Furthermore, although our approach enhances interpretability by modeling abstract interaction patterns, the inherent complexity of the learned representations may still limit direct human interpretability, making further advancements in this direction an important research goal.

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A Dataset Statistics

Table 2 summarizes the statistical properties of the WN18RR and FB15K-237 datasets, which serve

as standard benchmarks for evaluating knowledge graph completion models. These datasets address critical limitations in their predecessors (WN18 and FB15K) by eliminating inverse relation leakage through rigorous filtering protocols (Toutanova and Chen, 2015; Dettmers et al., 2018).

- **WN18RR:** Derived from WordNet, this dataset emphasizes hierarchical lexical relationships (e.g., hypernymy, meronymy). Its compact relational schema (11 relations) and dense connectivity reflect the taxonomy-driven nature of linguistic ontologies.
- **FB15K-237:** Curated from Freebase, it captures diverse real-world interactions across 237 relations. The long-tail relation distribution and heterogeneous connectivity patterns pose significant challenges for generalization.

This statistical characterization provides critical context for interpreting experimental results in Section 4, where we analyze model performance under these contrasting learning paradigms.

B Evaluation Metrics

We employ rank-based metrics to assess prediction quality, namely Mean Reciprocal Rank (MRR) and Hits@N. Detailed definitions of these metrics are provided below:

- **Mean Reciprocal Rank (MRR):** This is the average of the reciprocal ranks of the correct entities over all test triples.
- **Hits@N:** For $N \in \{1, 3, 10\}$, this metric computes the proportion of test triples for which the correct entity is ranked in the top N.

The evaluation is conducted under the filtered setting, where candidate rankings exclude entities that form known true triples in the training, validation, or test sets.

C GNN Distillation Decay Selection

To thoroughly evaluate the impact of decay strategies within the GNN distillation process, we conducted experiments comparing linear decay and exponential decay on the FB15K-237 dataset, under controlled conditions. All configurations utilized four GNN layers to maintain consistent model depth, ensuring reliable comparisons across different strategies.

Dataset	# Entities	# Relations	Triple	# Train	# Validation	# Test
WN18RR	40,943	11	93,003	86,835	3034	3134
FB15K-237	14,541	237	310,116	272,115	17,535	20,466

Table 2: Statistics of the WN18RR and FB15K-237 datasets.

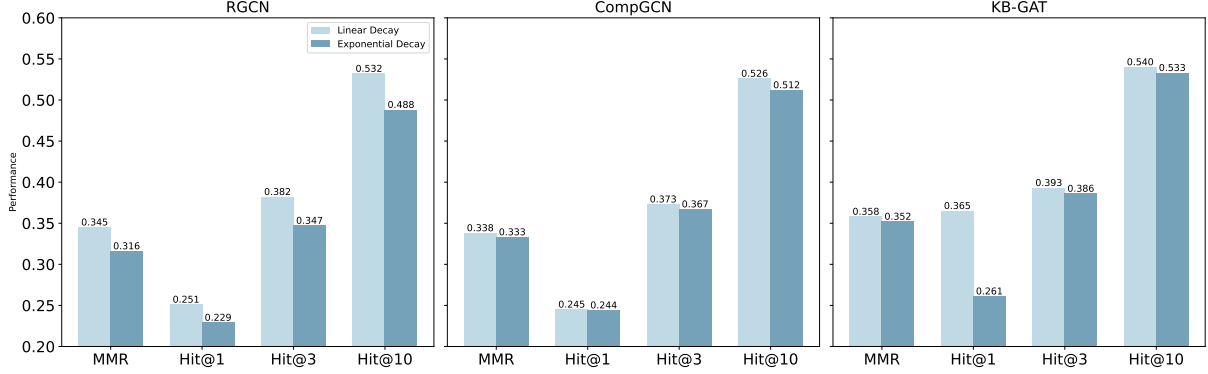


Figure 6: Comparison of linear and exponential decay strategies on the FB15K-237 dataset across three GNN distillation models.

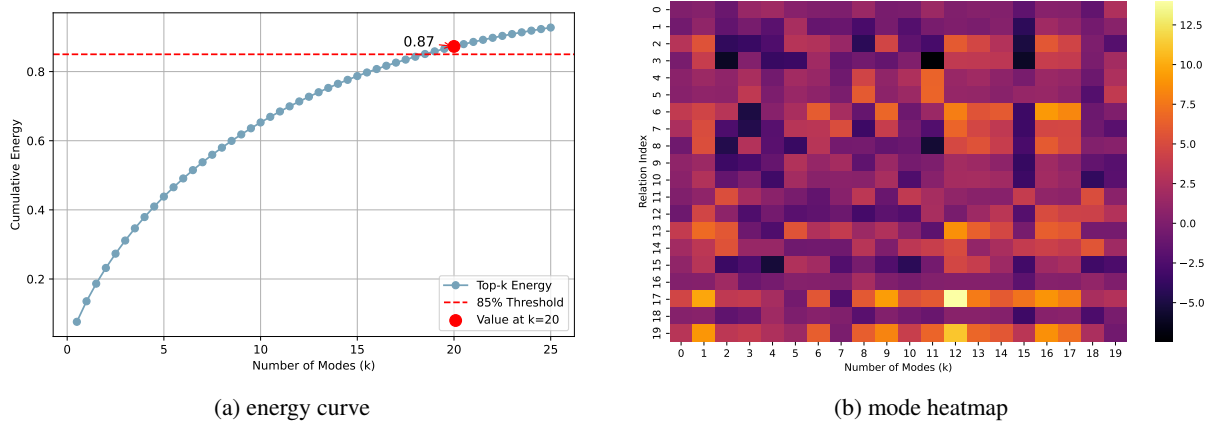


Figure 7: Mode retention validation results on FB15K-237 using CompGCN. In energy curve (a), the red dashed line marks the 85% threshold, and the blue line denotes the mean cumulative energy $\bar{E}(k)$. In mode heatmap (b), brighter hues indicate higher importance.

In the linear decay strategy, the filtering ratio was decreased by a fixed value of 0.2 per layer, starting from 1.0 and gradually reaching 0.4 after three layers. This uniform decrement allowed for a progressive refinement of the messages passed between nodes, minimizing abrupt shifts in representation quality. In contrast, the exponential decay approach used a decay factor of 0.74, which caused the filtering ratio to initially decrease more rapidly and then plateau, ultimately converging to a similar final value of approximately 0.4 after three iterations.

The performance results, as shown in the corresponding figures, demonstrate that the linear decay

strategy outperforms exponential decay in most models. This indicates that the steady, predictable reduction of features offered by the linear approach allows the network to better preserve essential discriminative features, compared to the sharper initial drop seen with exponential decay. Thus, the linear decay method provides a smoother transition in feature refinement, enabling the GNN layers to maintain a more balanced representation and achieve superior downstream performance.

These findings underscore the importance of carefully selecting the decay schedule to control feature propagation within GNN-based models. We demonstrate that even a simple strategy like linear

decay can significantly enhance representational fidelity, ultimately leading to improved performance in knowledge graph completion tasks.

D Mode Retention Validation

To rigorously validate that the Top-20 interaction modes preserve $\geq 85\%$ of the signature information, we conducted a two-stage analysis using trained model outputs: (i) cumulative energy retention calculation (ii) mode importance scoring.

In the first stage, for each entity $e \in \mathcal{E}$, its interaction signature vector $\mathbf{a}_e \in \mathbb{R}^K$ is sorted in descending order:

$$a_{(1)} \geq a_{(2)} \geq \cdots \geq a_{(K)} \quad (14)$$

The cumulative energy retention for the top- k modes is computed as:

$$E(k) = \frac{\sum_{i=1}^k a_{(i)}}{\sum_{j=1}^K a_{(j)}} \quad (15)$$

The mean cumulative energy $\bar{E}(k)$ across all entities quantifies the global information preservation capability.

In the second stage, for each relation $r \in \mathcal{R}$, the importance of the top- k modes is measured by:

$$\mathbf{I}(r, k) = \mathbb{E}_e \left[\mathbf{a}_e[k] \cdot \sum_{j=1}^K \mathbf{P}_r[k, j] \right] \quad (16)$$

where $\mathbf{P}_r[k, j]$ is the relation-specific transition matrix of the j -th mode being retained, and the \mathbb{E}_e denotes the expected value over all entities.

We conducted experiments on the FB15K-237 dataset using the CompGCN model, and the results are shown in Figure 7. The energy curve shows the Top-20 mode selection robustly preserves $\geq 85\%$ of signature energy across heterogeneous knowledge graphs, satisfying the $\geq 85\%$ retention threshold with statistical significance. The heatmap analysis confirms that distinct relations rely on specialized subsets of modes, demonstrating the framework’s capacity to adaptively capture relation-specific semantics. This dual visualization approach — combining cumulative energy trends with relation-mode importance mapping — provides both macroscopic and granular evidence for the efficacy of Top-20 mode selection. The methodology balances interpretability, computational efficiency, and theoretical rigor, establishing a principled foundation for sparse interaction modeling in knowledge graph completion.